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RESEARCH ARTICLE

Economic efficiency of rainfed wheat farmers under changing climate: evidence from Pakistan

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Abstract
Rainfed wheat farming directly depends upon climatic indicators and is mostly at the mercy of climatic extremes. This study analyzed the relationship between the economic efficiency of rainfed wheat farmers and indicators of climate variability in Pakistan employing a two-stage methodological framework. We used farm household level crop input-output and management data and secondary data on climate. In the first stage, a stochastic production frontier (SPF) approach was used to calculate economic efficiency. Then, in the second stage, the calculated economic efficiency scores were regressed against the temperature threshold, temperature anomaly, and total rainfall, in addition to socioeconomic, institutional, and farm variables, using OLS and quantile regression models. The results showed that temperature anomaly and the number of days when temperatures exceed 30 °C have negative and significant impacts on the economic efficiency of rainfed wheat farmers. Total rainfall showed positive and significant impacts across both OLS and quantile regression models. Further, we modeled a novel and very important variable in the context of rainfed wheat production in Pakistan, that is, farmers' participation in trainings in climate-resilient crop farming. This variable showed a positive and highly significant impact on economic efficiency of wheat farmers across all regression models. Our findings call for important policy implications, including developing up-to-date climate resilient adaptation strategies that are particularly focused on rainfed wheat farming. Establishing strong linkages between extension departments and rainfed wheat farmers could help sustain and improve the efficiency of rainfed wheat farmers and hence food and livelihood security.

Keywords Climate variability · Economic efficiency · Rainfed wheat · Stochastic production frontier · Quantile regression · Climate resilient crop farming

Introduction

Climate change is a major global problem. The problem is serious since the adverse impacts of changing climate can be sensed farther than the place that instigates it (Fahad et al. 2016). Crop farming businesses depend upon and are extremely vulnerable to climate variability, which significantly distresses crop productivity (Ahmed et al. 2018). The literature suggests that climate change is likely to result in substantial productivity losses for various crops, and the pace of these losses is expected to increase with the passage of time (Challinor et al. 2014; Rosenzweig et al. 2014; Knox et al. 2012). A loss of 25% is predicted in the short term depending upon the crop type and the region under investigation, while some studies have also projected losses of up to 50% by 2080 (Challinor et al. 2014; Knox et al. 2012). Studies have already reported that, in fact, climate change has already started to affect the crop production, with an estimation of 1 to 10% yield losses, matched by the state of absence of climate change (Lobell et al. 2011; Lobell and Field 2007). Climatic variability not only affects the crop productivity but also directly affects the livelihoods of masses that rely on crop production as their primary source of income. The potentially adverse impacts of climate change on crop productivity and the

The original article was revised: The correct Equation 4 is presented in this paper

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income levels of farming communities are projected to become a reason for a 20% increase in the population of hungry people through 2050 (Carty and Magrath 2013).

The impact of climatic change on crop productivity is highly heterogeneous in nature. It ranges from extremely severe impacts on lower and middle-income tropical and developing economies to minor (or even positive) impacts on temperate and developed nations (IPCC 2014). Approximately one-third (~ 32–39%) of world crop yield variability is described by climate variability, which could increase to more than 60% in the absence of immediate and appropriate adaptation (Ray et al. 2015). The situation could be even more alarming for rainfed crop farming since it is heavily centered on two important climatic parameters: temperature and rainfall. This fact means that if there are sufficient rains and favorable temperatures for crop growth, then the yields will be optimally close to the potential. Otherwise, the situation could be the reverse, even in the presence of the optimal use of all necessary inputs for crop production. Rainfed crop farming is of utmost importance as the area under and the staple food production from rainfed farming are 80% and 70%, respectively, with significant contributions from low-income and developing economies (Bradford et al. 2017).

The issue of climate change is particularly critical in South Asia as the region is serving as a shelter for approximately 30% of the world's undernourished people (Lobell et al. 2008). South Asian cereals production sector is under heavy warning due to climate change with other factors including soil health and water shortage (Yadav et al. 2016). Moreover, number of studies also investigated the stochastic effects of climate change on net crop income (Hossain et al. 2019a, 2019b). The impacts of climate change not only cause a reduction in farm produce and farm revenues but also caused a reduction in farmland values (Arshad et al. 2017b; Hossain et al. 2020). Wheat is being cultivated on 30.42Mha in India, 8.58 Mha in Pakistan, 0.76 Mha in Nepal, and 0.48 Mha in Bangladesh (FAOSTAT 2018). South Asian countries are facing the consequences of climate change in the form of heat waves, frequent floods, and droughts leading to crop failures and receding water tables (IPCC 2007). The occurrence of severe weather events has become more significant and violent since last couple of decades in South Asia. An increase of day and night-time temperatures have also been recorded at various weather observatories in Asian countries includes Sri Lanka, India, Nepal, and Pakistan (Sheikh et al. 2015).

Pakistan is among the most affected countries due to climate change with increasing vulnerability to climate change over time, although the country is contributing negligible amounts to global warming. Pakistan was ranked 12th, 8th, and 7th in 2012, 2015, and 2016, respectively, by Climate Risk Index (Kreft et al. 2017). Greater than normal temperatures have been recorded recently in various South Asian cities. Table 1 shows the states of extreme temperatures in Pakistan compared with other South Asian countries:

Despite Pakistan's recent slight moves toward industrialization, agriculture is still the dominant sector of the economy. This is because of heavy dependence of various manufacturing industries on the agriculture sector for raw materials. The share of the agriculture sector in the country's gross domestic product (GDP) is 18.9% and provides working prospects to 42.3% of the country's population (GOP 2018). Over the last couple of decades, climate variability and extreme weather events have badly affected rural livelihoods and the yields of major crops, such as wheat, rice, cotton, and sugarcane (Abid et al. 2015).

Although there have been a handful of studies of climatic change and its likely impacts on crop farming in Pakistan (Arshad et al. 2017b; Ahmed et al. 2018), the climate change impacts on rainfed farming have not yet been measured. The present study, therefore, is an attempt to estimate the impacts of climate change on the economic efficiency of rainfed wheat farmers in Pakistan since wheat is the main staple crop grown in this area. There have been considerable studies of the adverse impacts of climatic change on the yield of wheat (Mondal et al. 2013; Krupnik et al. 2015). When the temperature exceeds 30 °C, it disturbs the photosynthesis process in wheat plants, stimulating early maturity and causing reduced grain filling and yield losses (Asseng et al. 2011; Lobell et al. 2012). The wheat is the main cereal crop of the country and a key source of calorific consumption for the masses in Pakistan. Wheat has the largest area under cultivation compared with other crops cultivated in the country (GOP 2018). The area, production, and yield along percentage changes in area, production, and yield over the last 5 years are reported below in Table 2.

The aforementioned table shows a decrease of 1.9% in the area under cultivation, while the decreases in production and the yield of the wheat are 6% and 4.1%, respectively, for 2017–2018. In addition to decline in area under wheat cultivation, the main reason for enormous decreases in the production and yield of wheat was the acute shortage of water to irrigate the wheat (GOP 2018). As a result, one can imagine the importance of rains for the wheat in rainfed areas where there is no other source of irrigation available for watering the crop. Rainfed farming in Pakistan is of high importance since, of the total of 23 Mha of cultivated land, approximately 4 Mha of the total cultivated area are under rainfed farming. Approximately 33% of the wheat is cultivated in the rainfed zone of the country, and wheat has the highest area under cultivation than any other crop in the rainfed zone of Pakistan (Baig et al. 2013). Since wheat is the main crop of the region, wheat production and the efficiency of wheat farmers are under high risk with changing climatic conditions, which could ultimately lead to food insecurity.

Table 1 Selected cities of South Asian countries with historical temperature trends

South Asian city (country)	Average maximum temperature[a]	Change in temperature over time
Jacobabad (Pakistan)	53.0 °C	0.36 °C ↑ per decade
Pachpadra (India)	50.6 °C	0.68 °C ↑ per century
Manang (Nepal)	46.4 °C	0.12 °C ↑ annually
Rajshahi (Bangladesh)	45.1 °C	0.5–1 °C ↑ annually
Anuradhapura (Sri Lanka)	39.9 °C	0.01–0.036 °C ↑ annually

(*Source:* Naveendrakumar et al. 2019)

A few studies have already been conducted on adaptations to climate change and their determinants (Abid et al. 2015; Mahmood et al. 2020), crop insurance against weather extremes (Arshad et al. 2016), and agronomic field studies based on crop simulation modeling in Pakistan (Ahmad et al. 2015; Ahmed et al. 2018). Arshad et al. (2018) studied the effects of climate change on the yield and efficiency of rice and wheat farmers separately through diverse agro-ecological zones of Pakistan employing statistical methods. Some of the recent studies also focused on climate change impacts with particular emphasis on CO_2 emissions' effects on cereal crops in Pakistan (Ahsan et al. 2020; Chandio et al. 2020). These studies focused on short-term and long-term prospects of climate change impacts, primarily for rice and wheat in Pakistan, using econometric modeling approaches. A study of the effects of climate-smart farm practices (CSFPs) was conducted in the Punjab province of Pakistan to investigate the impacts of these practices on farm net revenue by considering endogeneity and selection bias effects (Shahzad and Abdulai 2020). However, there is not even a single study explicitly focusing on wheat in the rainfed agro-ecological zone of Pakistan, where there is no canal irrigation network. Moreover, wheat farming in this zone is totally at the mercy of two important climatic parameters, which are unpredictable rainfall and fluctuating temperatures. The novelty of the present study is centered on the inclusion of a previously unnoticed institutional variable, which is the training offered by the extension department in climate-resilient crop farming, including the use of heat-tolerant wheat varieties. One cannot produce higher crop yields by merely using crop inputs. Participation in training in up-to-date and climate-smart crop farming offered by institutes can play a significant role in achieving higher and more efficient output levels of a particular crop.

The wheat is cultivated not only as a food crop but also as a cash crop and crop production in Pakistan produces approximately 42.3% of rural households' expendable income (GOP 2018). This means that better wheat yield will lead to higher income levels that could be further utilized for farm households' expenses on health, education, and living. Likewise, this income could also be used on other business initiatives, and all of them eventually affect different development ventures of rural households (Amjath-Babu et al. 2016).

In 2018, the FAO cited a 4.4% reduction in wheat production in Pakistan as matched to the previous year, and it also emphasized the very uncertain prospects of the wheat in 2019 due to the acute shortage of water (FAO 2019). Water scarcity further increases the vulnerability of rainfed wheat farming because of its reliance on rains for water requirements due to the unavailability of supplemental irrigation systems. Given these facts, we find it pertinent to measure the effect of climate change on the economic efficiency of the yet unexplored rainfed wheat farming systems of Pakistan. This study also adds to the existing literature on the effect of climatic change on wheat productivity by investigating how climatic parameters (including temperature anomaly, total rainfall, and the number of days when temperature surpasses the crop-specific threshold level) affect the economic efficiency of rainfed wheat farmers in Pakistan, maintaining an assumption of ceteris paribus. Hence, it is the first study with a sole

Table 2 Area, production, and yield of wheat in Pakistan

Year	Area		Production		Yield	
	(000 ha)	% change	(000 tons)	% change	(kg/ha)	% change
2013–2014	9199	6.2	25,979	7.3	2824	1.0
2014–2015	9204	0.1	25,086	− 3.4	2726	− 3.5
2015–2016	9224	0.2	25,633	2.2	2779	1.9
2016–2017	8972	− 2.7	26,674	4.1	2973	7.0
2017–2018	8797	− 1.9	25,076	− 6.0	2851	− 4.1

Source: Ministry of Food and Agriculture, Federal Board of Statistics emphasis on rainfed wheat farming in Pakistan. This fact makes this study different from other studies conducted either at provincial levels (Abid et al. 2015) or across diverse agro-ecological zones of Pakistan (Arshad et al. 2018). In this zone-specific study, we analyze the effects of climatic variability in a region where the farming and farmers efficiency mainly depend upon temperature and rainfall. The analysis of this study comprises two steps. In the first step, the economic efficiency of 400 rainfed wheat farmers is calculated. Then, in the second step, the study assesses how climatic variability distresses the economic efficiency of rainfed wheat farmers by regressing the calculated economic efficiency scores on climatic, socioeconomic, and farm variables. Hence, the objective of the present study is to investigate the impacts of specific temperature threshold, total rainfall, and temperature anomaly (i.e., variation in the observed wheat growing season's mean temperature from the historical mean) on the economic efficiency of rainfed wheat farmers in Pakistan. The findings of the present study add to the existing literature from Pakistan by exclusively providing the efficiency of rainfed wheat farmers and the impact of climate variability on the economic efficiency of wheat farmers in a yet unexplored agro-ecological zone of Pakistan, i.e., the rainfed zone. Moreover, the present study also models a very important institutional variable, i.e., "trainings attended by the farmers in climate-resilient crop farming," in the analyses. The rationale for modeling this variable is to determine its impact on the economic efficiency of rainfed wheat farmers, in addition to climatic variables and set of other explanatory variables used in the analysis.

The rest of the paper has been structured as follows. The second section of this paper describes the study area, the explanatory variables used in this study, and the methodological framework for conducting the analyses. The third section presents the results and discussion. Finally, the fourth and last section provides conclusions and policy implications based on the results.

Methods and materials

Primary data collection

Pakistan has been divided into 12 different agro-ecological zones by Pakistan Agricultural Research Council. All 12 agro-ecological zones differ from each other based on climate, soil characteristics, socioeconomic traits, and, to an even greater extent, the different crops being cultivated in these zones. Figure 1 shows all of the agro-ecological zones of Pakistan.

This study focuses on wheat for two reasons. First, wheat is the major crop according to the area under cultivation in the rainfed zone; and second, wheat is the main staple crop of the rainfed zone and of the country as well. Through a detailed review of the literature and climate-related studies already conducted across various agro-ecological zones in Pakistan, a comprehensive questionnaire was designed for the present study. Then, this questionnaire was tested by conducting a preliminary field survey to exclude irrelevant information and include the most relevant questions in the context of the area under investigation. Furthermore, the questionnaire was also improved on the basis of discussions with agricultural field officers working in respective areas. Finally, a well-prepared and pretested questionnaire was used for data collection from wheat growers in 2017, employing a multistage random sampling technique. A trained team of enumerators was hired for the questionnaire's pretesting and then for the final data collection. The sampling procedure consisted of five steps. In the first step, the rainfed zone was exclusively selected as the main study area. In the second step, four *districts* (main administrative unit) out of thirteen *districts* were randomly selected from whole rainfed zone. In the third step, one *tehsil* (sub-administrative unit) from each *district* was randomly chosen. In the fourth step, one *union council* from each *tehsil* was randomly selected. Finally, in the fifth step, we randomly selected and interviewed 100 wheat farm households from each *union council,* resulting in 400 farm households in total from the whole rainfed zone of Pakistan. The survey data contained detailed information regarding crop input-output quantities with respective prices, crop management data, farm characteristics, institutional variables data, and socioeconomic data from farm households. The description of the variables used in stochastic production frontier analysis and later for quantile regression analysis is provided below (see Table 3).

Collection and processing of secondary data and threshold setting

Time series data on temperature and rainfall for the last 38 years (1980–2017) for the wheat growing period were collected from meteorological stations located in the study area, compiled by the Pakistan Meteorological Department (PMD) (PMD-Pakistan Meteorological Department, 2017). We plotted historical mean seasonal temperatures (1980–2016) and current mean seasonal temperature (2017) for wheat (Fig. 2), showing a 1.86 °C increase in current mean compared with historical mean.

The data for wheat growing season (November to April) were abstracted from the time series data of the last 38 years. We calculated the medium-term climatic variability for the wheat, which is the variation in the observed wheat growing season's mean temperature from the calculated historical mean. Total rainfall was also calculated for the wheat growing season from sowing to harvesting. Considering heat-sensitive threshold levels, days with temperature > 30 °C during the

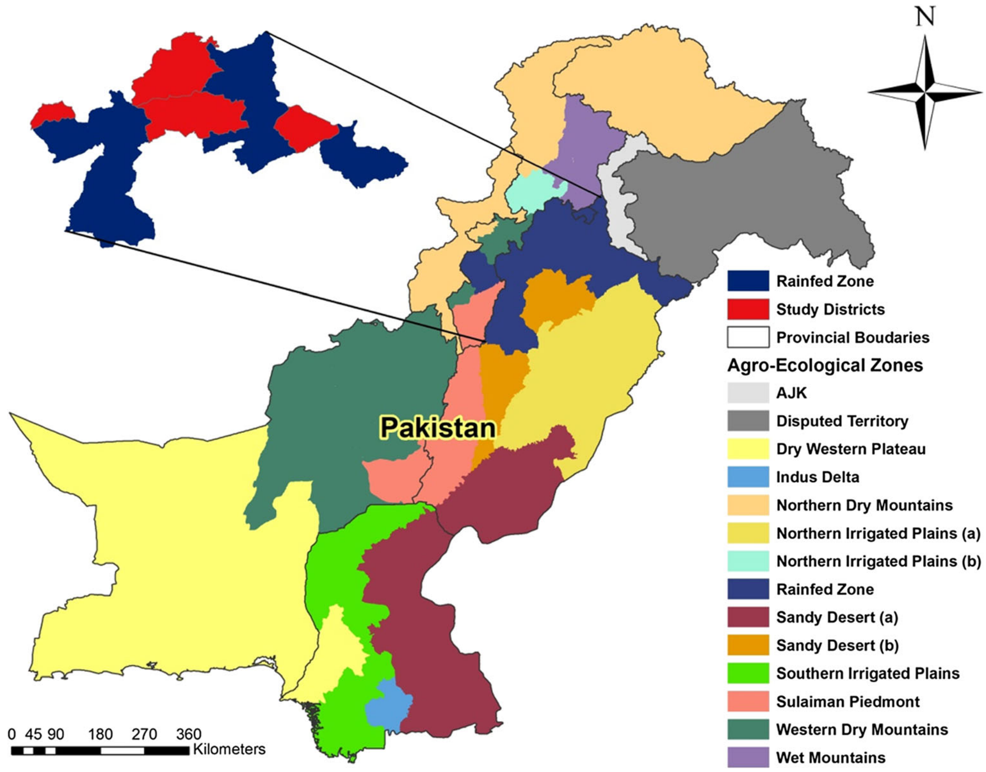

Fig. 1 Map of Pakistan with all 12 agro-ecological zones and study zone highlighted in blue and districts in red

wheat growing season, which is strongly related to quicker senescence (Asseng et al. 2011; Lobell et al. 2012), were calculated for the entirety of the wheat growth period in 2017 (the wheat season for which field surveys were conducted).

Methodological framework

A two-step method was used to determine the impacts of climate change on the economic efficiency of rainfed wheat farmers. In the first step, we estimated the efficiency score of each farm household. Then, in the next step, we regressed the calculated efficiency scores against variables of climate change and heat stress, as well as socioeconomic and farm characteristics. In the first step, a stochastic production frontier (SPF) model was employed for calculating the economic efficiency. Instead of calculating only the technical efficiency of rainfed wheat farmers, the present study investigated economic efficiency to depict a better picture of climate change's impacts on farmers' food and livelihood situations. Another reason for using inputs in monetary terms is that rational farmers always attempt to maximize output, ultimately leading to profit maximization. As a result, all of the variables were used in economic terms (i.e., input costs and wheat revenues, obtained from selling wheat grain and wheat straw) to estimate the economic efficiency of each farm household. Based on previous research work in South Asia and especially in Pakistan, we also assumed that the farm households are very much aware of climate change. They make various adaptations accordingly based on their experience of historical trends in temperature, rainfall, and crop productivity (Abid et al. 2016; Arshad et al. 2017a). By opting for better crop management practices under climatic variability to minimize the costs while maximizing crop yields, farm households can achieve progressively economically efficient levels on the frontiers.

In the second step of the analysis, first ordinary least square (OLS) and then quantile regression analysis were employed to determine the relationships of parameters of climate change and heat stress with farm households' efficiency scores. The quantile regression model is based on the conditional quantiles of the dependent variable, instead of the overall mean of the dependent variable. This approach provides a very precise estimation of the relationship between the dependent variable (efficiency scores) and explanatory climatic, socioeconomic, and farm characteristics data. It also allows the researcher to investigate the relationship between a set of explanatory variables and different parts of the distribution of the variable of interest (efficiency scores, in this case).

Stochastic production frontier (SPF) model

The stochastic production frontier (SPF) model has been extensively used to measure the efficiency for various crops including wheat (Battese et al. 2017; Arshad et al. 2018). The generalized form of stochastic production frontier for the ith farmer can be described as:

Table 3 Summary statistics of the variables used in the stochastic production frontier (SPF), OLS and quantile regression analyses

Variables	Unit	Mean	Std. dev.	Minimum	Maximum
Variables used in SPF analysis					
Dependent variable					
Gross revenue of wheat	US$ ha^{-1}	651.93	250.18	209.26	2042.74
Explanatory variables					
Total cultivated area	ha	2.60	2.24	0.41	15.38
Seed cost	US$ ha^{-1}	38.48	6.89	3.81	89.06
Chemical protection measures cost	US$ ha^{-1}	13.93	5.08	1.78	34.73
Fertilizer cost	US$ ha^{-1}	57.39	20.22	3.13	94.39
Land preparation plus labor cost	US$ ha^{-1}	91.31	45.52	16.03	168.30
Land rent	US$ ha^{-1}	131.01	28.14	71.24	231.52
Variables used in OLS and quantile regressions					
Dependent variable					
Economic efficiency of rainfed wheat farmers	Scores	0.73	0.13	0.36	0.95
Explanatory variables					
Number of family members	*N*	5.12	1.77	1	12
Age of farm household[a]	Dummy	0.21	0.41	0	1
Distance from input market	km	8.86	5.58	0.5	25
Soil type[b]	Dummy	0.18	0.38	0	1
Trainings attended[c]	Dummy	0.26	0.44	0	1
Total area under rainfed wheat	ha	2.60	2.24	0.41	15.38
Variation in the observed wheat growing season's mean temperature from historical mean	°C	1.88	1.69	0.01	4.60
Days with temperature > 30 °C during wheat growing season	*n*	37.25	10.22	25	53
Total rainfall during the wheat cropping season	mm	145.74	44.26	71.02	178.70
Total observations	400				

Note: [a] represents *1* for young farmers, otherwise *0*; [b] indicates *1* for clay soil, otherwise *0*; and [c] denotes *1* for participation in trainings in climate-resilient wheat farming including the use of heat tolerant varieties, otherwise *0*

$$y_i = f\ (x_i; \beta) + \varepsilon_i, where\ i = 1, 2, \ldots.., n. \tag{1}$$

In the above equation, the error term can be further divided into two parts—random noise (v_i) and inefficiency (u_i)—and can be stated as:

$$y_i = f\ (x_i; \beta).\exp\ (v_i).\exp\ (-u_i), where\ i = 1, 2, \ldots., n \tag{2}$$

In Eq. (2), x_i represents the crop inputs, y_i is the yield of the *i*th farmer, $f\,(x_i, \beta)$ is the deterministic part of the output function, where β represents unknown parameters that are required to be measured, and exp.(v_i) is the stochastic part of the output

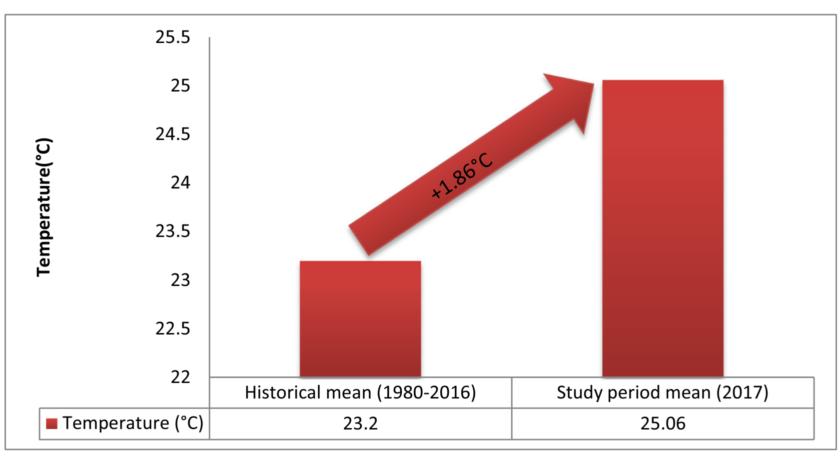

Fig. 2 Comparison of historical (1980–2016) and current (2017) temperature means

function, which accounts for statistical noise and is related to random factors that are out of farmers' control. The stochastic production frontier (SPF) is based on the assumption of symmetrical distribution with a mean value equal to zero. Finally, the second part of the error term (u_i) accounts for inefficiency, and it is presumed to be free from v_i to fulfill the constraint $u_i \geq 0$. The stochastic production frontier model gives the economic efficiency scores (θ) and estimates (β) of all of the parameters.

We calculated (θ) following Lovell (1993) as:

$$\theta_i = \frac{y_i}{[f\ (x_i;\beta).\exp\{v_i\}]} = \exp\{-u_\mathrm{i}\}, \qquad i = 1, 2, \ldots, n. \tag{3}$$

The choice of the functional form is very much essential before conducting SPF analysis, and for this reason, the appropriateness of the functional form is checked. We tried two functional forms for $f\,(x_i,\ \beta)$ in Eq. (2) containing the Cobb-Douglas functional form, compared with translog specification. For this purpose, the log-likelihood ratio (LR) test is used as below:

$$\mathrm{LR} = -2\{\text{Log Likelihood }(\mathrm{H_o})\text{–Log Likelihood }(\mathrm{H_1})\}$$

The results of the LR test are shown in Table 4, rejecting the Cobb-Douglas specification at $\alpha = 5\%$ and selecting the translog specification as an appropriate functional form.

Translog specification is more flexible than the Cobb-Douglas functional form. The translog stochastic production frontier for the present study can be written as:

$$\begin{aligned}\ln yi = {} & \beta_o + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \beta_3 \ln x_3 + \beta_4 \ln x_4 \\ & + \beta_5 \ln x_5 + \beta_6 \ln x_6 + ½\beta_7 \ln x_1^2 + ½\beta_8\ \ln x_2^2 \\ & + ½\beta_9 \ln x_3^2 + ½\beta_{10} \ln x_4^2 + ½\beta_{11} \ln x_5^2 + ½\beta_{12} \ln x_6^2 \\ & + \beta_{13} \ln x1 \ln x2 + \beta_{14} \ln x_1 \ln x_3 + \beta_{15} \ln x_1 \ln x_4 \\ & + \beta_{16} \ln x_1 \ln x_5 + \beta_{17} \ln x_1 \ln x_6 + \beta_{18} \ln x_2 \ln x_3 \\ & + \beta_{19} \ln x_2 \ln x_4 + \beta_{20} \ln x_2 \ln x_5 + \beta_{21} \ln x_2 \ln x_6 \\ & + \beta_{22} \ln x_3 \ln x_4 + \beta_{23} \ln x_3 \ln x_5 + \beta_{24} \ln x_3 \ln x_6 \\ & + \beta_{25} \ln x_4 \ln x_5 + \beta_{26} \ln x_4 \ln x_6 + \beta_{27} \ln x_5 \ln x_6 \\ & + (v_i–u_i)\end{aligned} \tag{4}$$

where y_i depicts the gross revenue per hectare and the vector of x variables represents crop inputs and output statistics, i.e., area under wheat cultivation (x_1), seed cost (x_2), fertilizer cost (x_3), chemical protection measures cost (x_4), land preparation (including plowing, planking, sowing) plus labor cost (x_5), and land rent (x_6), where applicable. β_o is the intercept of the model, which is constant. The terms β_1 to β_{27} are the unknown parameters, which are required to be estimated, and v_i is a random error and is independently and identically distributed $\{N\ (0,\sigma_v^2\ )\}$. Maximum likelihood estimates (MLEs) and θ were calculated utilizing STATA software, version 15.1. All of the crop inputs have been used in terms of their costs following the mean exchange rate of US\$1 = 105.90 PKR (2017).

Ordinary least square (OLS) and quantile regression analyses

The second step of the analysis consisted of OLS and quantile regression models to determine the effects of temperature and rainfall parameters on the efficiency of wheat farmers. For this purpose, we regressed the variation in the observed wheat growing season's mean temperature from the historical mean, number of days having a temperature greater than 30 °C (indicative of heat stress), and total rainfall for the whole growth period of the wheat against the famers' economic efficiency scores. Our analyses are based on the assumption that rainfed wheat farmers are cognizant and have already adjusted their farming practices and management decisions in light of the changes in total rainfall rates and variation in the observed wheat growing season's mean temperature from the historical mean and heat stress (i.e., number of days with temperature > 30 °C).

The rationale for including the observed and historical data on climatic parameters is that the economic efficiency of wheat farmers is partially influenced by the crop's reaction to present weather conditions and partially by the farm households' management decisions based on their past experience (Arshad et al. 2017a; Abid et al. 2016). It has been widely observed and reported that farmers adopt various management practices based on the experience and observed changes in temperature and rainfall rates. Major adaptation techniques include changing crop variety, changing time of sowing, and changing the time and composition of different crop inputs and supplemental irrigation.

Table 4 Results of the log-likelihood ratio test to select the functional form of the model

Null hypothesis	Log likelihood value ($\mathrm{H_o}$)	Test value (λ)	Critical value	Accept/reject
$\mathrm{H_o}$: $\beta_{ij} = 0$	− 136.267	81.64	32.67 (21)	Reject $\mathrm{H_o}$: Translog is appropriate

Table 5 Stochastic production frontier (SPF) results of rainfed wheat production

Variable	Variable description	SPF estimates (β_i)
lnx_1	*ln* (wheat cropped area in ha)	− 1.9346**(β_1)
lnx_2	*ln* (seed cost in US$ ha^{-1})	− 0.5372(β_2)
lnx_3	*ln* (chemical protection measures cost in US$ ha^{-1})	1.8163*(β_3)
lnx_4	*ln* (fertilizer cost in US$ ha^{-1})	− 0.7466917(β_4)
lnx_5	*ln* (land preparation plus labor cost in US$ ha^{-1})	3.7186***(β_5)
lnx_6	*ln* (land rent in US$ ha^{-1})	9.4629**(β_6)
½ ($ln^2_{x_1}$)	½ {*ln* (wheat cropped area)}^{2}	0.0377(β_7)
½ ($ln^2_{x_2}$)	½ {*ln* (seed cost)}^{2}	0.6278*(β_8)
½ ($ln^2_{x_3}$)	½ {*ln* (chemical protection measures cost)}^{2}	0.1835**(β_9)
½ ($ln^2_{x_4}$)	½ {*ln* (fertilizer cost)}^{2}	0.04651(β_{10})
½ ($ln^2_{x_5}$)	½ {*ln* (land preparation plus labor cost)}^{2}	0.2445**(β_{11})
½ ($ln^2_{x_6}$)	½ {*ln* (land rent)}^{2}	− 1.0855*(β_{12})
$lnx_1\times lnx_2$	*ln* (wheat cropped area) × *ln* (seed cost)	0.1979(β_{13})
$lnx_1\times lnx_3$	*ln* (wheat cropped area) × *ln* (chemical protection measures cost)	0.3157***(β_{14})
$lnx_1\times lnx_4$	*ln* (wheat cropped area) × *ln* (fertilizer cost)	0.08343(β_{15})
$lnx_1\times lnx_5$	*ln* (wheat cropped area) × *ln* (land preparation plus labor cost)	− 0.0244(β_{16})
$lnx_1\times lnx_6$	*ln* (wheat cropped area) × *ln* (land rent)	0.0221(β_{17})
$lnx_2\times lnx_3$	*ln* (seed cost) × *ln* (chemical protection measures cost)	0.0858(β_{18})
$lnx_2\times lnx_4$	*ln* (seed cost) × *ln* (fertilizer cost)	− 0.0884(β_{19})
$lnx_2\times lnx_5$	*ln* (seed cost) × *ln* (land preparation plus labor cost)	− 0.3404*(β_{20})
$lnx_2\times lnx_6$	*ln* (seed cost) × *ln* (land rent)	− 0.0424(β_{21})
$lnx_3\times lnx_4$	*ln* (chemical protection measures cost)× *ln* (fertilizer cost)	− 0.0325(β_{22})
$lnx_3\times lnx_5$	*ln* (chemical protection measures cost)× *ln* (land preparation plus labor cost)	0.0611(β_{23})
$lnx_3\times lnx_6$	*ln* (chemical protection measures cost)× *ln* (land rent)	− 0.6022**(β_{24})
$lnx_4\times lnx_5$	*ln* (fertilizer cost)× *ln* (land preparation plus labor cost)	− 0.0445(β_{25})
$lnx_4\times lnx_6$	*ln* (fertilizer cost)× *ln* (land rent)	0.2362(β_{26})
$lnx_5\times lnx_6$	*ln* (land preparation plus labor cost)× *ln* (land rent)	− 0.6912***(β_{27})
σ^2		0.2086***
Gamma (γ)		0.8291***
Mean value of economic efficiency of rainfed wheat farmers(θ)		0.73

*, **, and *** indicate the level of significance at *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$, respectively

A quantile regression model is an excellent substitute for simple OLS regression (Koenker and Bassett 1978; Leider 2012) since it is useful for explaining the detailed relationship between various explanatory variables and the variable of interest (i.e., dependent variable). OLS regression estimates the effect of explanatory variables only on the mean of the conditional distribution of the response variable, while quantile regression allows the slope estimates to fluctuate at various points of the conditional distribution of the response (Halkos and Skouloudis 2019). Most importantly, quantile regression is a robust method because it provides reliable estimates even in the presence of outliers (John 2015). The presence of even a single outlier in the data set can greatly change the slope of the coefficient, rendering its estimations unreliable. Hence, the quantile regression analysis overcomes this problem efficiently due to its robustness property. Quantile regression is extremely helpful for estimating any segment of the dependent variable's distribution, thus simplifying a richer elucidation of the association between variables that might poorly exist or even not exist at all (Arshad et al. 2018). Hence, we reported the results of estimated parameters of both OLS regression and quantile regression for 0.25, 0.50, 0.75, and 0.95 quantiles. A significant number of studies have investigated the impacts of CO_2 emissions on various economies in a variety of ways (Dogan and Turkekul 2016; Moutinho et al. 2018) and the impacts of atmospheric concentration of CO_2 on crop farming, in addition to other climatic variables (Fitzgerald et al. 2016). Despite its robustness, the quantile regression model has a limitation in that it does not allow for the inclusion of atmospheric concentration of CO_2 in its calibration.

We regressed the economic efficiency of rainfed wheat farmers against heat stress (i.e., total number of days with temperature > 30 °C during the wheat growing season) and variation in the observed wheat growing season's mean temperature from the historical mean and total rainfall in both OLS and quantile regression models. We also included some socioeconomic, institutional, crop management, and farm variables in both models as controls (Table 3). A significant number of early 1990s farm studies (Ali and Flinn 1989; Parikh et al. 1995) employing SPF models. These studies investigated how different socioeconomic factors, farm features such as farm size, institutional variables in the form of various types of extension services, and farm households' education impacted the efficiency of crop growers in Pakistan (Parikh et al. 1995). Therefore, we included the aforementioned aspects in the present analyses.

We first ran an OLS multiple regression model on a vector of explanatory variables (E_i) containing particular socioeconomic, institutional, crop management, farm features, and climatic data to investigate the effect of all of these variables on economic efficiency scores (θ_i):

$$\theta_i = \widehat{\beta}o + \widehat{\beta}_1 E_{i1} + \ldots. + \widehat{\beta}_{in} E_{in} + \widehat{u}_i \tag{5}$$

Then, we ran the quantile regression following Koenker and Bassett Jr (1978) and Arshad et al. (2018):

$$\theta_i = \quad X_i^T + \beta_\tau + \mu_{\tau i}, \mu_{\tau i} \sim D_{\tau i} \text{ subject to } D_{\tau i}\ (0) = \tau \tag{6}$$

where θ_i is the response variable (economic efficiency score) estimated from the stochastic production frontier (SPF) model in first step of the analysis. Whereas i in the aforementioned equation is the index of the individual farm household, X denotes the vector of covariates for i. The quantile particular effects are given by β_τ for a given quantile: $0 < < 1$. In Eq. (6), the unknown error term $\mu_{\tau i}$ is featured by the total distribution function $D_{\tau i}$. The quantile regression model in Eq. (6) also describes the quantile function $Q_{\tau i}$ ($\tau|X_i$) of the response variable θ_i conditioned on a vector of explanatory climatic parameters X_i in a given quantile τ. The quantile function can be described as:

$$Q_{\tau i}\left(\sqrt{\tau} X_i\right) = D_{\theta_i}^{-1}\left(\sqrt{\tau} X_i\right) = X_i^T \tag{7}$$

The conditional quantile can be explained as a problem of optimization (Koenker and Bassett Jr 1978) as follows:

$$\underset{\beta_\tau}{argmin} \sum_{i=1}^{n} \rho_\tau \left(\theta i - X_i^T \beta_\tau\right) \tag{8}$$

where ρ_τ is the "check function" that accounts for both positive and negative terms of a quantile disproportionately. Eq. (8) is solved using the "qreg" package in STATA.

Results and discussion

Estimates of stochastic production frontier (SPF) model

The estimated mean economic efficiency of rainfed wheat farmers in the 2017 growing season via stochastic production frontier employing the maximum likelihood method was 73%. The mean economic efficiency of rainfed wheat farmers is much lower than the combined mean economic efficiency of wheat farmers (91%) across all agro-ecological zones of Pakistan, as reported by Arshad et al. (2018). The low score of mean economic efficiency of the rainfed wheat farmers is mainly due to the rainfed wheat zone heavily relying on seasonal rainfall to fulfill crop water requirements, while most of the other wheat-producing zones have well-structured, canal-based supplemental irrigation systems.

The findings of the stochastic production frontier are presented in Table 5, along with their signs and significance levels. The values of the independent variables in the production function were mean corrected. Therefore, the first-order parameters ($\ln x_1$, $\ln x_2$,…, $\ln x_6$) could be stated as output elasticities with respect to the individual explanatory variables at the mean input values. The economic efficiency of rainfed wheat farmers showed negative and significant relationships with the area under wheat cultivation. This result is in fact in line with some previous studies (Holst et al. 2013; Poudel and Kotani 2013) reporting a negative relationship between wheat yield and area under wheat cultivation, implying that small farms and farmers are more efficient than their larger counterparts. Further studies reported that the area under a particular crop is often negatively related to efficiency because of resource utilization less than optimum levels (Sial et al. 2012). Small famers tend to use available resources more efficiently, ultimately leading to inverse associations between the area under cultivation and the value of production (Sial et al. 2012). The theory of induced innovation (Hayami and Ruttan 1985) hypothesizes that small farmers implement the types of approaches that alleviate production constraints and improve the land utilization available for cultivation through optimal use of various inputs, ultimately causing an increase in their efficiency (Oduol et al. 2006). However, the reverse also occur since some studies have also reported that small farms are less productive than large ones (Sheng et al. 2019; Sheng and Chancellor 2019), demonstrating the heterogamous behavior of the relationship between farm size and farmers productivity and ultimately with their efficiency.

The results of the stochastic production function approach showed heterogeneous behavior of inputs used for wheat cultivation. The chemical protection measures' cost (β_3) showed a positive and significant relationship with economic efficiency of rainfed wheat farmers. The coefficients of seed cost (β_2) and fertilizer cost (β_4) were not significant in their first order.

Table 6 Results of ordinary lease square (OLS) and quantile regression models for the economic efficiency of rainfed wheat production

Variable	OLS estimates	Quantile regression estimates			
		0.25	0.50	0.75	0.95
Number of family members (*n*)	− 0.0032	0.0325	− 0.0037	− 0.0039	− 0.0063**
Age of the farm household (dummy)[a]	0.0318**	0.0229	0.0306	0.1440	0.0151
Distance from input market (km)	− 0.0034**	− 0.0041**	− 0.0019	− 0.0099	− 0.0004
Soil type (dummy)[b]	0.0456**	0.0449	0.0820*	0.0360	−0.0026
Trainings attended (dummy)[c]	0.0724***	0.1103***	0.0852***	0.0429**	0.0227*
Variation in the observed wheat growing season's mean temperature from historical mean (°C)	− 0.0045	− 0.0148	− 0.0123**	− 0.0017	0.0109
Days with temperature > 30 °C during wheat growing season (*n*)	− 0.0028***	− 0.0033	− 0.0034**	− 0.0022*	− 0.0021***
Total rainfall during the wheat cropping season (mm)	0.0003**	0.0006**	0.0029*	0.000017	0.0001
Constant	0.8112***	0.699***	0.8474***	0.9258***	0.9858***
R^2 and pseudo R^2 for OLS and quantile regressions, respectively	0.1377	0.1082	0.1106	0.0421	0.0342
Total observations	400				

[a] represents *1* for young farmers, otherwise *0*; [b] indicates *1* for clay soil, otherwise *0*; and [c] denotes *1* for participation in trainings in climate-resilient wheat farming including the use of heat tolerant varieties, otherwise *0*. (*, **, and *** show the level of significance at $*p < 0.1$, $**p < 0.05$, and $***p < 0.01$, respectively)

This could be due to the use of these inputs below the recommended level since the square of the seed cost (β_8) showed a positive and significant impact on the economic efficiency of rainfed wheat farmers.

This outcome indicates that there is still a large scope for increasing the economic performance of wheat by increasing the seed rate and chemical crop protection measures since the variable still showed a positive and significant relationship with economic efficiency in its squared form (β_9). However, some farm households in the study area used the recommended levels of the various crop inputs, but it was quite impossible to determine the optimal level of input use beyond any increase in the level of input use not showing any increase in output level (Krupnik et al. 2004).

Therefore, for the accurate quantification of these impacts under farm households' own field management practices, more research is warranted before advising optimum input applications and better crop management strategies to boost the wheat productivity in rainfed areas of Pakistan. The land rent (β_6) showed a positive and significant relationship with economic efficiency, indicating that the economic performance of the crop increases with an increase in land rent. Ricardo suggested that farmland prices are directly related to the productivity of agricultural land (Ricardo 1817), indicating that more productive lands have high land rents and ultimately show high economic performance of a particular crop. However, the squared term of land rent (β_{12}) showed a negative relationship with economic efficiency, indicating that too high land rents do not truly represent the value of land productivity. Rather, these values are more representative of better locations of particular pieces of land, for example, easy access to the input markets and transportation (Czyżewski and Matuszczak 2016). The variable of land preparation plus labor cost (β_5), along with its squared term (β_{11}), showed a positive relationship with the economic efficiency of rainfed wheat farmers. This means that the more time that is spent, and more money is invested to prepare the field, resulting in higher yield (Koondhar et al. 2018) and ultimately leading to higher economic performance of rainfed wheat.

Table 5 also shows some quite interesting results of second-order parameters (i.e., interaction terms between explanatory variables). The interaction term of the area under wheat cultivation and chemical protection measures costs (β_{14}) showed positive impacts on economic efficiency of the wheat farmers. This indicates that an increase in the use of chemical crop protection measures, along with increased area under wheat cultivation, caused an increase in the economic performance of rainfed wheat farmers for the study period. The interaction term of seed cost and land preparation plus labor cost (β_{20}) showed a negative relationship with economic efficiency. The interaction term of chemical protection measures' cost and land rent (β_{24}) and the interaction term of land preparation plus labor cost and land rent (β_{27}) showed negative impacts on the economic efficiency of rainfed wheat farmers.

Our results showed that increased input use causes an increase in wheat productivity and ultimately increases the economic efficiency of rainfed wheat farmers. Increased use of inputs, however, must be well supported by experimentally based research studies to avoid the declining trend in economic efficiency due to the diminishing marginal returns against one of these inputs, for example, fertilizer use (Krupnik et al.

2004). Most importantly, increased input use must be coupled with best crop management practices (e.g., optimal rate and timing of fertilizer use; recommended levels of chemical crop protection measures, such as pesticides, herbicides, and fungicides; and sincere efforts toward increasing the soil's organic matter). Otherwise, blind increases in input use without coupling with the aforementioned best farm management practices could result in unwanted environmental problems that ultimately destabilize efforts toward sustainable crop farming (Patra et al. 2016). Therefore, paying greater attention is very crucial when devising policy to increase productivity, followed by increased economic efficiency of the rainfed wheat farmers. This is also important because rainfed agriculture is already facing manifold problems, such as soil erosion, moisture stress, weed intensification, nutrient deficiency, and poor nutrient use efficiency, ultimately limiting the yield potential of rainfed areas of Pakistan in general and rainfed wheat in particular (Baig et al. 2013).

Climate change and economic efficiency of rainfed wheat farmers

The estimates of the OLS regression model show that temperatures > 30 °C during the whole growing period of wheat had a significant ($p < 0.01$) and negative effect (coefficient − 0.0028) on the economic efficiency of rainfed wheat farmers in Pakistan (Table 6). The total number of days with recorded temperatures > 30 °C were 37 (± 10 SD) during the whole wheat growing period, reflecting confirmation of the harmful impacts of heat stress elsewhere in South Asia (Krupnik et al. 2015; Arshad et al. 2018). The reduction in mean wheat yield levels due to rising temperature has been documented by various studies (Holst et al. 2013; Husnain et al. 2018; Mahmood et al. 2019). The same trend was observed for the middle (50th), higher (75th), and highest (95th) economic efficiency quantiles for rainfed wheat farmers in Pakistan, with $p < 0.01$ (coefficient − 0.0034), $p < 0.1$(coefficient − 0.0022), and $p < 0.05$ (coefficient − 0.0021), respectively. The impact of heat stress in the form of number of days > 30 °C on the economic efficiency of rainfed wheat farmers through these quantiles was negative, supporting the research work on the overall significance of the sensitivity and vulnerability of wheat against temperature increases, especially in developing areas (Mondal et al. 2013; Arshad et al. 2018).

Total rainfall (145 ± 44 mm SD) had a significant ($p < 0.05$) and positive effect on the economic efficiency of rainfed wheat farmers in the OLS regression. Total rainfall had a positive and significant impact on the economic efficiency of rainfed wheat farmers in the lower (i.e., 25th) and middle (i.e., 50th) economic efficiency quantiles, at $p < 0.05$ for both. A recent study conducted in mixed agro-ecological zones of Pakistan also reported similar results (Arshad et al. 2018). Positive and significant effects of total rainfall reveal its importance to rainfed farming systems in Pakistan since they are totally dependent on rain for crop water requirements. This also indicates that the crop performance and livelihood security of the rainfed region are heavily centered upon favorable weather conditions in the form of suitable temperature conditions and sufficient rains for good crop growth. The variation in the observed wheat growing season's mean temperature from the historical mean (i.e., temperature anomaly) did not show any substantial effect in the OLS regression. However, it negatively affected the efficiency of rainfed wheat farmers in the middle (i.e., 50th) quantile. A number of studies have recommended various agronomic measures to manage the problem of heat stress for South Asian wheat farmers. These measures, among the major ones, include heat-resistant crop varieties, supplement irrigation, and early sowing to escape high temperatures (Krupnik et al. 2013; Abid et al. 2015). The major reason for including temperature in the form of temperature anomaly and number of days when temperature exceeded 30 °C was to obtain a clearer picture of rising temperatures' impacts on the economic efficiency of rainfed wheat farmers, instead of modeling the mere average temperature, which sometimes does not provide accurate impacts.

In addition to the parameters of climate variability and heat stress, the farmers' family size negatively influenced the economic efficiency of rainfed wheat farmers in highest (95th) quantile, although the variable was not significant in OLS regression and other quantiles but still had a negative coefficient in the majority of the quantiles. The reason for this negative relationship is that a large family size provides more laborer units, including skilled and unskilled members. The supply of this labor from large families sometimes results in a situation of more labor than required and ultimately causing a decline in output per laborer unit. This decrease in output per laborer unit would ultimately cause a decrease in the economic efficiency of a particular laborer unit. We used a dummy variable for household's age ("1" for young farmers and "0" for old farmers), which showed a positive effect on the economic efficiency of rainfed wheat farmers in the OLS regression only. This is due to the reason that young farmers are more active and efficient in performing various labor tasks on farms than older farmers. The result is in line with the result of a study conducted in Thailand, which investigated how young farmers caused an increase in overall technical efficiency on farms (Saiyut et al. 2019). The input market access (calculated as distance from the input market in kilometers) negatively influenced the economic efficiency of rainfed wheat farmers in the OLS regression and in the lower (25th) quantile. Easy and timely access to input markets helps farmers to obtain information about best crop management and suitable adaptation practices (Abid et al. 2015), further helping to increase crop productivity (Katungi et al. 2011; Mahmood et al. 2019) and ultimately their economic efficiency. Clay soils positively influenced the economic efficiency of rainfed wheat farmers in the OLS regression and in middle (50th) quantile of economic efficiency. This positive impact is due to clay soils having greater water holding capacity and rainfed wheat meeting their water requirements from moisture retained by these soils from the previous rains. The availability of ample moisture required for ideal crop growth will result in better crop yields and cause an increase in the economic efficiency of rainfed wheat farmers. Most importantly, the variable "trainings attended" (i.e., farmers' participation in trainings in "climate-resilient wheat farming" and "use of heat-resistant wheat varieties") showed a very strong relationship with economic efficiency. The variable significantly and positively influenced the economic efficiency of rainfed wheat farmers with $p > 0.01$, $p > 0.01$, $p > 0.01$, $p > 0.05$, and $p > 0.1$ in OLS regression and the lower (25th), middle (50th), higher (75th), and highest (95th) quantiles of economic efficiency of rainfed wheat farmers. The trainings were conducted by the agricultural extension department at regular intervals during the year of the study (i.e., 2017). The significant role of access to and availability of general extension services for improving the economic efficiency of the wheat farmers under climate variability and heat stress has already been reported in previous studies conducted in South Asia, including Pakistan (Arshad et al. 2017a, 2017b; Ullah et al. 2020). However, the present study pointed out the importance of a special extension service, that is, trainings in climate-resilient wheat farming, including the use of heat-resistant wheat varieties, particularly in the rainfed zone of Pakistan. A recent study also emphasized the importance of climate-specific extension services for doing sound adaptations against climate change to attain sustainable wheat production levels (Mahmood et al. 2020). The performance of the crop farming sector could further be improved through the proper communication of advanced knowledge of climate-resilient agriculture among the agents working in the field of crop production (Vincent et al. 2015) since climate-resilient crop farming is an essential ingredient for regional and global food security (Dhankher and Foyer 2018).

Limitations of study

The present study findings are totally based on 1-year field survey data due to unavailability of a panel data set for the studied area. An in-depth study could be conducted using more detailed information with additional variables through the availability of panel data sets in the future. Another limitation of the present study is that the temperature variable was used in its two forms (i.e., temperature anomaly and number of days when temperature exceeds 30 °C) by considering the overall growth period of the wheat. A detailed picture could be captured by considering the temperature conditions at different phenological growth stages of the wheat. Due to methodological limitations, the model used in this study did not allow the inclusion of atmospheric concentration of CO_2 in its calibration.

Conclusion and policy recommendations

This study adds to the existing research on the impacts of heat stress and climate change on rainfed wheat cropping systems in Pakistan. We estimated the impacts of specific temperature thresholds, total rainfall, and the variation in the observed wheat growing season's mean temperature from the historical mean on the economic efficiency of rainfed wheat farmers in Pakistan. Instead of only investigating the general climate change impacts on rainfed wheat, the present study first calculated the economic efficiency of rainfed wheat farmers. Then in the second step, the impacts of climate variability and the temperature threshold on calculated economic efficiency scores were analyzed. The findings indicated that the total rainfall and specific temperature threshold during the crop growth period do affect the economic efficiency of the rainfed wheat farmers. The positive impact of rainfall and negative impact of rising temperature and specific temperature thresholds on the economic efficiency of rainfed wheat farmers indicate the importance of developing drought- and heat-tolerant wheat varieties to avoid yield losses due to climate change in the studied region. These findings also highlight the importance of special policy formulations for the strong extension efforts needed to enhance the efficient production and, hence, rural livelihoods and food security. More importantly, the results of the present study accentuate the importance of training programs in climate resilient crop farming and the use of heat-resistant wheat varieties since this variable showed a strong and positive relationship with the economic efficiency of rainfed wheat farmers. Inclusion of the variable "training programs in climate resilient crop farming" in our analyses rendered this study different from the previous ones, which mainly focused on the importance of the access and availability of general extension services.

Along with adaptations such as early sowing, changing input use combinations, use of heat-resistant crop varieties, use of better management practices such as rainwater harvesting, and up-to-date and advanced farmers' trainings in climate resilient farming can truly help farmers to escape from the adverse impacts of increasing heat and climate variability. The positive impacts of better input market access and farmers' age on the economic efficiency of rainfed wheat farmers show that agronomic strategies alone might not be sufficient until coupled with some socioeconomic and institutional considerations. Therefore, farmers' socioeconomic and physiological parameters, along with strong extension energies for creating farmers' awareness of the importance and fruitful impacts of climate resilient crop farming, are required to improve the economic efficiency of rainfed wheat production. Furthermore, highlighting the importance of sound adaptation measures and best crop husbandry practices are also required to cope with reduced wheat production, as well as reduced farm income. If the farmers' income is reduced due to heat stress and climate variability, then they will not be in a position to spend reasonable amounts of money to obtain better health facilities for their families and good education facilities for their children. Hence, sound agricultural policy formulations are required to improve the farmers' financial position through improved farm income, which would ultimately improve the rainfed wheat farmers' ability to make agronomic adaptations against climate change.

Future studies could be conducted on farmers' awareness and adaptation of climate smart practices to cope with climate change in a better way. Since rainfed wheat farming is totally dependent upon the rains, future research endeavors could be focused on work related to rainwater harvesting potential and its ultimate impacts on rainfed crop farming. These focuses could further help rainfed farmers to consider the options of double cropping and crop diversification. Climate-specific advisory services and their ultimate impacts on the food and livelihood security of the rainfed region could be the next steps after farmers' participation in climate-resilient crop farm trainings. Similar studies could be conducted in other agro-ecological zones of Pakistan to see more detailed spectra of the impacts of climate change and heat stress on the economic efficiency of wheat farmers. Likewise, the results of present study could also be validated in different South Asian territories with similar climatic conditions.

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